Science of the Total Environment 651 (2019) 2036–2043

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Integrating management information with soil quality dynamics to monitor agricultural productivity

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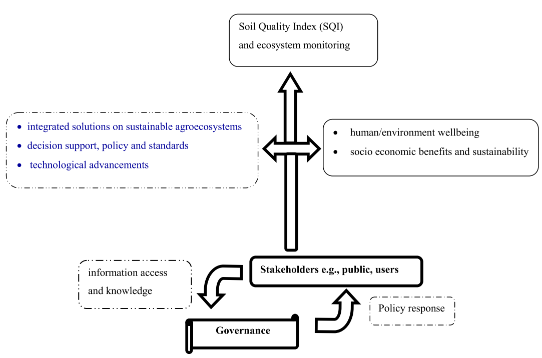
HIGHLIGHTS

- Explication of new technique for diagnosing and monitoring soil quality
- Identified 4 soil physical and chemical properties influencing soil quality
- Soil quality index (SQI) and the crop yields are highly correlated.
- New SQI effective for monitoring agricultural productivity

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 24 July 2018
Received in revised form 7 October 2018
Accepted 8 October 2018
Available online 9 October 2018

Editor: Filip M.G. Tack

Keywords:
Land management
Monitoring
Soil use
Soil quality index

ABSTRACT

Sustainably utilizing global resources is critical for ensuring soil security which is pertinent for biomass production, climate change mitigation, environmental quality, biodiversity conservation and thus human wellbeing. A plethora of soil quality assessment metrics encapsulated in different concepts exist, with each typically biased towards identifying the interrelationship between agricultural production and specific physical, chemical or biological soil attributes. Because of diversity in soil classifications and crop requirements, considerable variation exist between these metrics making it difficult for end-users to select a suitable method. Here, Partial Least Squares Regression (PLSR) method is used to integrate the physical and chemical soil properties into a Soil Quality Index (SQI) which is then used to evaluate soil quality dynamics vis-à-vis crop yields over two growing seasons. Field data was acquired from 5 sites under No-Till (NT), Conventional Till (CT) management and Natural Vegetation (NV) land use. This SQI was computed under the hypothesis that site specific soil physico–chemical attributes depended on soil type, management, and depth. Under CT management P_w (Pewamo silty clay loam) had the highest soil quality; KbA (Kibbie fine sandy loam) soils had higher quality under NT management; whereas CtA (Crosby Celina silt loams) had relatively higher quality under NV land use. Soil bulk density (ρ_b), Soil Organic Carbon (SOC), Available Water Content (AWC) and Electrical Conductivity (EC) were the significant soil parameters influencing soil quality. The correlation between SQI and corn (*Zea mays*) yields was 0.6, whereas SQI and Soybean (*Glycine max* (L.) Merr.) yield was 0.9. Future research will evaluate SQI dynamics vis-à-vis socio-economic indicators and key climate variables.

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https://doi.org/10.1016/j.scitotenv.2018.10.106
0048-9697/

1. Introduction

Recent global analyses have highlighted the link between soil quality versus food, water, energy security and poverty, and have documented trends in soil degradation and biodiversity decline (Finzi et al., 2011; Lal, 2014). Soil degradation is linked to severity of floods, landslides, disease outbreaks that has in turn lead to social unrest, displacement of people and socio-economic decay (Lal, 2016; Paz-Ferreiro and Fu, 2016). About one billion people suffer from chronic hunger, one-quarter of this population residing in sub-Saharan Africa (FAO, 2013). The conflicting information from existing monitoring frameworks delay early detection and mapping of indiscriminate land management practices, thereby enhancing the societal vulnerability to environmental disasters caused by uncertain climate, drought stress, or recurring eutrophication observed in the Florida coast, Chesapeake Bay, and Lake Erie (U.S.) (de Paul Obade and Moore, 2018; de Paul Obade et al., 2013). Indeed, abrupt climate change and burgeoning human populations are expected to impose even greater pressure on the finite soil and water resources, thereby accelerating negative trends and threatening socio-economic prosperity (Lal, 2016; Paz-Ferreiro and Fu, 2016). As depicted in Fig. 1, credible scientific information are required by stakeholders (e.g., policy makers and the public) to evaluate management impacts on soil resources, support framing of action plans and guide decision making and policy. Implementation of policies to protect finite soil resources is constrained, in part, by: (i) lack of consistent yet structured identification of sensitive soil attributes reflecting soil multi-functionality because of complexity and site-specificity of soils, (ii) difficulties in comprehensively assessing the interrelationships between anthropogenic land management, soil quality dynamics, soil threats (e.g., erosion, sealing, biodiversity loss, salinization SOM decline etc.), functions (e.g., habitat provision, element cycling, biological regulation etc.) and soil based ecosystem services (e.g., biomass production, erosion control, pest and disease control, water quality and supply, climate regulation, biodiversity conservation), (iii) defining an operational concept of soil quality (Bünemann et al., 2018; de Paul Obade and Lal, 2016a, 2016b). Thus, standardized techniques that aggregate soil attributes sensitive to land management are required to monitor soil quality dynamics which depend on anthropogenic land use and management and to some extent extrinsic factors such as parent material, climate, topography, and hydrology (Bünemann et al., 2018; McBratney et al., 2014).

Soil quality definition which includes the physical, chemical and biological soil entities, encompasses the abiotic and biotic interaction of soil processes that sustain plant and animal productivity without adversely impacting on environmental quality (Andrews et al., 2002a, 2002b; Doran and Parkin, 1994). Although sometimes used interchangeably, soil quality focuses on the soil capacity to satisfy human needs such as produce food from crops, whereas soil health refers to the soil's capacity to continually sustain plant growth and maintain soil's functions (Bünemann et al., 2018). Soil quality varies with depth, nutrient cycling dynamics and leaching (Jobbágy and Jackson, 2004). Although a plethora of methods and indicators exist for characterizing soil quality, there is hardly a universal soil quality metric (de Paul Obade and Lal, 2013, 2014b; de Paul Obade et al., 2013). Even with the advances in monitoring technologies, reporting soil quality changes is still fraught with uncertainties attributable to data artifacts, indeterminate baselines, model deficiencies and validation challenges (Andrews and Carroll, 2001; de Paul Obade and Lal, 2014a; Finzi et al., 2011; Karlen et al., 1997; Mota et al., 2014; Nortcliff, 2002). The proliferation of data, indicators, and models has created a surfeit of information, making it difficult for end-users to understand impacts of land management decisions on soil systems, let alone identify the most appropriate assessment methods especially for below ground soil processes (Jobbágy and Jackson, 2001). Because soil quality determines ecosystem functions, screening out a minimum dataset to inform on the magnitude, location and direction of soil quality changes is critical for strategizing remedial measures before irreversible damage occurs (Bouma, 2015; Bouma and McBratney, 2013; McBratney et al., 2014).

Soil quality information may rudimentarily be assessed by: (i) visual examination (i.e., soil color) and plant rooting depth, (ii) soil compactness, (iii) soil tilth, and (iv) crop yields (Fierer et al., 2007; Karlen et al., 1998). Soil Organic Carbon (SOC) concentration, is ubiquitous as a soil quality indicator, not only because it optimally typifies soil biota

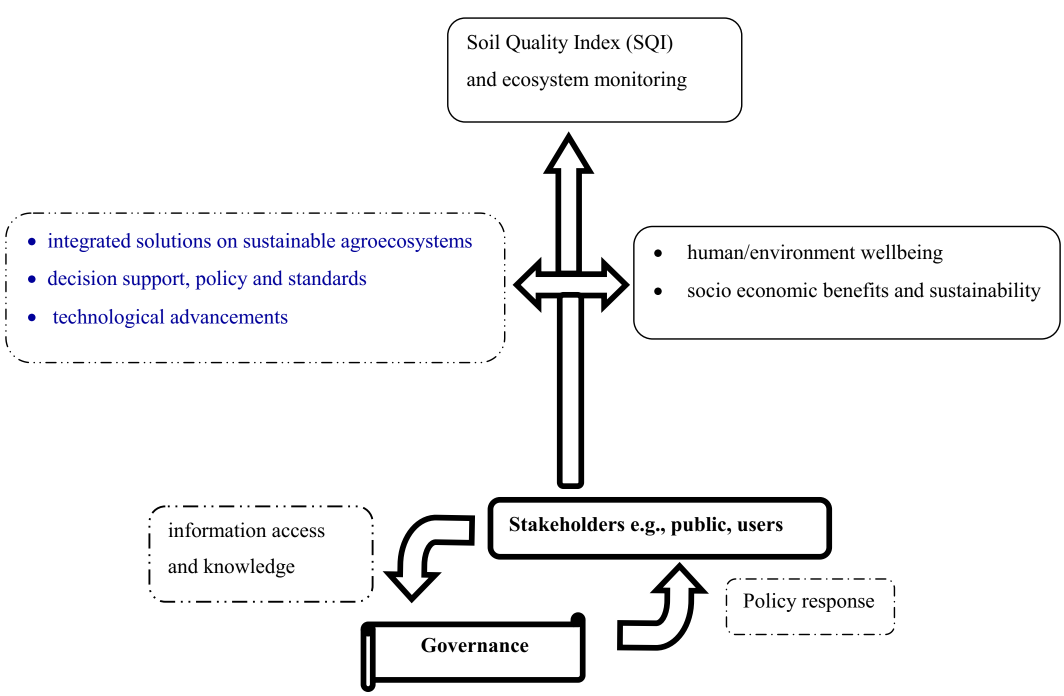

Fig. 1. Conceptual framework for Soil Quality Index (SQI) comprised of governance and stakeholders to support scientific based decision making and policy for sustainable agro-ecosystem management.

dynamics but also because it plays a key role in fertility, soil water availability and aggregate stability, in croplands (Bouma and McBratney, 2013; Lal, 2002, 2004, 2009; Lal, 2013; Obade, 2012; Ohlson, 2014). Blecker et al. (2012) posited that a comprehensive soil quality determination should include activity and composition of soil microbial communities which are known to be very sensitive to soil quality changes and environmental conditions. However this specification can be impeded by biases such as sample contamination and the relatively high costs of taxonomic interpretations (de Paul Obade and Lal, 2014a, 2014b; Fierer et al., 2007; Stockmann et al., 2014). The Cornell Soil Health Test offers different soil testing packages with supplementary fact sheets and scoring cards to assess soil degradation and health. Soil quality metrics should be tailored to specific applications, for instance, in croplands, the challenge remains how to relate soil quality dynamics with specific functions.

Although much progress has been made in identifying the complex soil problems, there has been mixed success in development of objective soil quality monitoring metrics, creating a gap between what science can offer and the information decision makers need to understand consequences of anthropogenic decisions on soil ecosystems (McBratney et al., 2014). To this end, synthesis of complex qualitative and quantitative soil information using a soil quality index (SQI) can be beneficial for evaluating soil threats and management impacts on soil functionality (Bünemann et al., 2018). SQIs synthesize measured soil attributes into a simplified format for downstream science applications, land management applications and policy formulation (Bünemann et al., 2018; Wienhold et al., 2004). In principle, indicators should be sensitive to changes over time, refer to benchmark or threshold values, be predictive or anticipatory and convey relevance to the stated objectives of assessment (Bünemann et al., 2018; Vollmer et al., 2016, 2018). Although well designed indices may offer a powerful management and communication tool, they are also prone to oversimplifying complex phenomena, and can only be useful if they can be unequivocally interpreted and optimal standard reference values are available (Bünemann et al., 2018; Vollmer et al., 2016, 2018). Because soil quality interpretation referencing subjectively selected benchmarks such as soils from native vegetation (i.e., which may not necessarily be fertile) is contentious, this research advocates for relative comparative assessment of SQIs aggregated from identical attributes of different soils.

Oftentimes soil quality information is a critical input in land evaluation models which describe land performance based on the link between agricultural production vis-à-vis soil quality, water availability, climate, topography, agro-ecological aptitude, socio-economic and environmental aspects (Arshad and Martin, 2002; Nguyen et al., 2015; Rosa, 2005). Land evaluation assesses the optimal allocation of land for different uses, thereby providing critical information useful for strategizing on land use options and sustainable land management (Bünemann et al., 2018). Whereas there is no ideal "one size fits all" approach for monitoring soil quality, synthesizing multivariate environmental and soil data from a wide range of spatial and temporal scales may facilitate identification and understanding of key variables driving soil processes (Larson and Pierce, 1994). Because soils are living entities that constitute a solid, liquid and gaseous phases, and is multifunctional (e.g., climate regulation, pollution control, biodiversity conservation, water/air purification, nutrient cycling, biomass production), simply selecting an individual soil property to infer soil quality is insufficient (de Paul Obade and Lal, 2016a, 2016b; Ohlson, 2014). Unlike the Soil Management Assessment Framework (SMAF) which utilizes score curves (and additive index) derived from perceived graphical relationships or literature review to evaluate management impacts on soil quality (Karlen et al., 2008; Wienhold et al., 2004), this study monitors soil quality using an SQI derived by partial least squares regression (PLSR). From a methodological standpoint, the non-parametric PLSR method is plausible because it: (i) distills significant attributes influencing soil quality, and (ii) objectively integrates qualitative (i.e., management) and quantitative (e.g., soil physical, chemical attribute) data to generate a concise model (Andrews and Carroll, 2001; Armenise et al., 2013; Mehmood et al., 2011, 2012). Based on the hypotheses that croplands soils and soils under natural vegetation (NV) land use are similar, and that SQI and crop yields are correlated, this research: (i) describes a novel approach for monitoring soil quality dynamics vis-à-vis crop yields under different management scenarios and (ii) discusses the limitations and promise of this approach and offers recommendations.

2. Materials and methods

2.1. Study area

The field data was sampled before planting from privately owned farmers' fields at the following locations within Ohio, USA: Miami (40° 10′ 12″ N, 84°07′ 41.7″ W), Seneca site 1 (41° 00′ 25″N, 83° 16′ 21″ W), Seneca site 2 (41° 12′ 43″ N, 82°54′ 39″ W), Preble (39° 46′ 09″ N, 84°36′ 52″ W and & 39° 41′ 45″N, 84°40′ 36″ W), and Auglaize (40° 27′ 34.5″ N, 84°26′ 14.8″ W) (Table 1). The total annual precipitation in Ohio averages between 90 and 125 cm, and the mean temperature varies between 8.1 and 10.7 °C (DeForest et al., 2012). However, meteorological drought was experienced in this Midwestern region in 2012 (year 1) (Lal et al., 2012) with a resultant decline in total rainfall by approximately 20 cm during the growing season (http://www.ncdc.noaa.gov/sotc/drought/2012/8#MRCC); but 2013 (year 2) had no drought. Other than NV land use, the predominant cropland management systems included the plowed or conventional till (CT) and no-till (NT) that minimally disturbs the soils. The surface residue cover was low (i.e., <30%) in CT managed fields compared with NT. The CT managed fields at Miami, Seneca, and Preble sites were chisel plowed to approximately 25 cm depth, except for the Auglaize site which was disked. NT management was practiced for >5 years in most plots, except Preble site which had sections under NT for over 25 years.

Corn (*Zea mays* L.) and soybean (*Glycine max* (L.) Merr.) were grown as per the specific agronomic practices in Ohio county (Table 1). No lime was applied in CT fields, except at Preble site where 3.7 Mg/ha was applied in NT fields. After planting, approximately 3.5 kg ha^{-1} of Atrazine herbicide was applied at Seneca (site 2), yet Seneca (1) had 84 g ha^{-1} of chlorimuron-ethyl benzoate and 124 g ha^{-1} flumioxazin to curtail weeds. Tillage and seeding tractor weights were approximately 10 and 6 Mg, respectively.

2.2. Sampling procedure

A total of 408 soil samples (i.e., 204 per year) were collected in April and early May, over 2 years from the P_w, GWA, kbA, CrA, and CtA soil types. The field reconnaissance, identification of soil series, and sampling zone selection was conducted using maps downloaded from the web soil survey (http://websoilsurvey.sc.egov.usda.gov/App/WebSoilSurvey.aspx). For intuitive consistency, each sampling point was geo-located with a global positioning system (GPS), and soils sampled from the same topographic slope (i.e., summit) within the NT, CT and NV management zones. Core and bulk soil samples were obtained at each management entity, from 3 randomly selected sampling points, located at the tips of an arbitrary 10 m × 10 m × 10 m equilateral triangle marked on the ground. The soil samples were acquired at 0–10, 10–20, 20–40, and 40–60 cm depth increments; totaling 12 samples per management class.

Hand harvesting of corn and soybean was done between August to October, on the exact GPS location in which the soil samples were obtained. The yield determination was as follows: (i) for corn, the ears from a dimension of 2 rows and 2 m long were hand harvested and weighed in the field; however, the soybean weight were measured from 1 m^2 dimension, (ii) the corn, and soybean were air dried, shelled, after which the dry weight of cobs, kennels, beans, and remaining above ground vegetative biomass measured. The plant water content was

Table 1
Field sampling locations within Ohio, USA.

Site	Coordinates	[a]Soil type	Management practices	NPK fertilizer kg ha^{-1}	Cover crops
Auglaize	(40° 27′ 34.5″ N, 84°26′ 14.8″ W)	P_w	NV, NT_{cc}, CT	50 kg ha^{-1} of liquid 28% N; and 20 Mg/ha pen pak (straw mixed with manure), and 247 Mg/ha free stall (animal manure) in April	Canadian oats (*Avena sativa*)
Miami	(40° 10′ 12″ N, 84°07′ 41.7″ W)	CrA	NV, NT, NT_{cc}, CT	50 kg ha^{-1} of 10-34-0 NPK in spring; 180 kg ha^{-1} of 28% liquid N, and 490 kg ha^{-1} in June	Wheat (*Triticum aestivum*)
Preble	(39° 46′ 09″ N, 84°36′ 52″ W) & (39° 41′ 45″ N, 84°40′ 36″ W)	CtA	NV, NT, CT	160:100:120	
Seneca (1)	(41° 00′ 25″ N, 83°16′ 21″ W)	kbA	NV, NT_{ccm}, NT_{cc}, CT	160:60:100	Grass
Seneca (2)	(41° 12′ 43″ N, 82°54′ 39″ W)	GWA	NV, NT_{cc}, CT	180:120:150	Grass

CrA (Crosby silt loam; taxonomic class: fine, mixed, active, mesic Aeric Epiaqualfs).
kbA (Kibbie fine sandy loam; taxonomic class: fine-loamy, mixed, active, mesic Aquollic Hapludalfs).
GWA (Glynwood silt loam; taxonomic class: fine, illitic, mesic Aquic Hapludalfs).
CtA (Crosby Celina loams; taxonomic class; fine, mixed, active, mesic Aquic Hapludalfs).
P_w (Pewamo silty clay loam: taxonomic class; fine, mixed, active, mesic Typic Argiaquolls).
cc, cover crop; m, manure.
NV, natural vegetation (Woodland).
CT, conventional tillage.
NT, no till.
csc: corn soybean corn.
ccs: corn corn soybean.
ch: corn hay.
c: corn.
NPK is nitrogen (N), phosphorus (P) and potassium (K).
[a] Soil types are described in the web soil survey (http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx).

determined after oven drying subsamples of kernel, cob and beans at 60 °C for 96 h; whereas the grain yields were calculated by adjusting the respective weights to 15.5% moisture for corn, and 13.5% for soybean. The Harvest Index (HI) was computed as the ratio of harvested grains, or beans to the total above ground vegetative biomass.

2.3. Soil analyses

Soil samples were collected, processed and analyzed as per the USDA-NIFA project (project web site: sustainablecorn.org) guidelines (Kladivko et al., 2014). Soil ρ_b was assayed using the core method, with stones and roots removed from the core which was filled with only soil. Soil moisture content was determined gravimetrically by oven drying a fraction of soil at 105 °C (Topp and Ferre, 2002). Water retention was determined by a combination of a tension table (Blanco-Canqui and Lal, 2007; Clement, 1996), and pressure plate extractors (Blanco-Canqui and Lal, 2007; Klute, 1986; Klute and Dirksen, 1986). The available water capacity (AWC) was computed as the difference in volumetric water content at field capacity (FC) (−33 kPa) and permanent wilting point (PWP) (−1500 kPa) (Dane and Hopmans, 2002; Jemai et al., 2013).

The soil pH and EC were measured in a 1:1 soil:water suspension (with a hand-held portable probe[2]) (Lal, 1996; Peech, 1965) from bulk disturbed air dried soil samples, which had been pulverized, and sieved through a 2-mm sieve. Inorganic carbonates were absent because the soil pH was approximately 7, thus SOC concentration was considered equivalent to total C (Brown et al., 2006; De Vos et al., 2005). Alternately, the Vario Max C:N analyzer was used to determine the total carbon/nitrogen (C/N) ratio by the dry combustion method at 900 °C, from soil passed through a 250 μm sieve (Nelson and Sommers, 1996). Total C and N stocks were computed by multiplying respective elemental concentrations, ρ_b and depth of soil layer. The nitrate and nitrite concentration were determined from fresh soil samples stored in cool conditions prior to analyses with Ion Chromatograph (Zhang et al., 2013).

[2] Thermo Scientific, Orion Star Series, Made in Singapore.

2.4. Model development

Partial Least Squares Regression (PLSR) computed using the *PROC PLS* in SAS 9.2 (SAS Institute Inc., Cary, NC, USA), at 5% significance level was used to relate 12 site characteristic predictor parameters (i.e., soil type, management (NT, CT, NV)), depth increments (0–10, 10–20, 20–40, 40–60 cm) to 10 soil physical and chemical response attributes (i.e., AWC, FC, PWP, soil ρ_b, EC, pH, nitrate, nitrite and SOC concentration, C/N ratio), under the hypothesis that site specific soil physical and chemical attributes depend on soil type, management, and soil layers. Initially the model "fits" and extracts regression coefficients or "equivalent weights" for specific soil type, management practices and soil layer based on measured soil physical and chemical values; which are aggregated into the Σ Soil Attribute Index (SAI), and subsequently converted to Soil Quality Index (SQI in %) (de Paul Obade and Lal, 2016a). Besides, (i) factor weights were used to identify important variables, (ii) differences in soil quality over two years assayed, (iii) SQI from croplands versus NV land use was compared, and (iv) the correlation between the SQI and crop yields was computed.

3. Results and discussion

3.1. Detailing critical soil attributes affecting SQI

Monitoring soil quality is pertinent for guiding policy decisions on sustainable agro-ecosystem management. The PLSR models had an accuracy of R^2 of 0.64 and 0.75; and a minimum Root Mean PRESS (predicted residual sum of squares) of 0.95 and 0.96 for year 1 and 2, respectively. The 1st factor having higher R^2 (coefficient of determination) was used for exploratory ranking of variables, because the first 3 factors from year 2 model had an R^2 of 0.90, 0.80 and 0.57; whereas year 1 had 0.83, 0.81 and 0.58, respectively. Fig. 2 shows the variation in factor weights for CT managed soils was significantly less than for NT or NV managed soils, and singles out SOC, EC, AWC and ρ_b (i.e., >5%) as the critical soil attributes influencing soil quality, an observation that can be inextricably linked to tillage practice, wheel traffic, fertilizer and pesticide applications. According to Dick (1983), mechanical insertion of fertilizer into the root is challenging in NT systems,

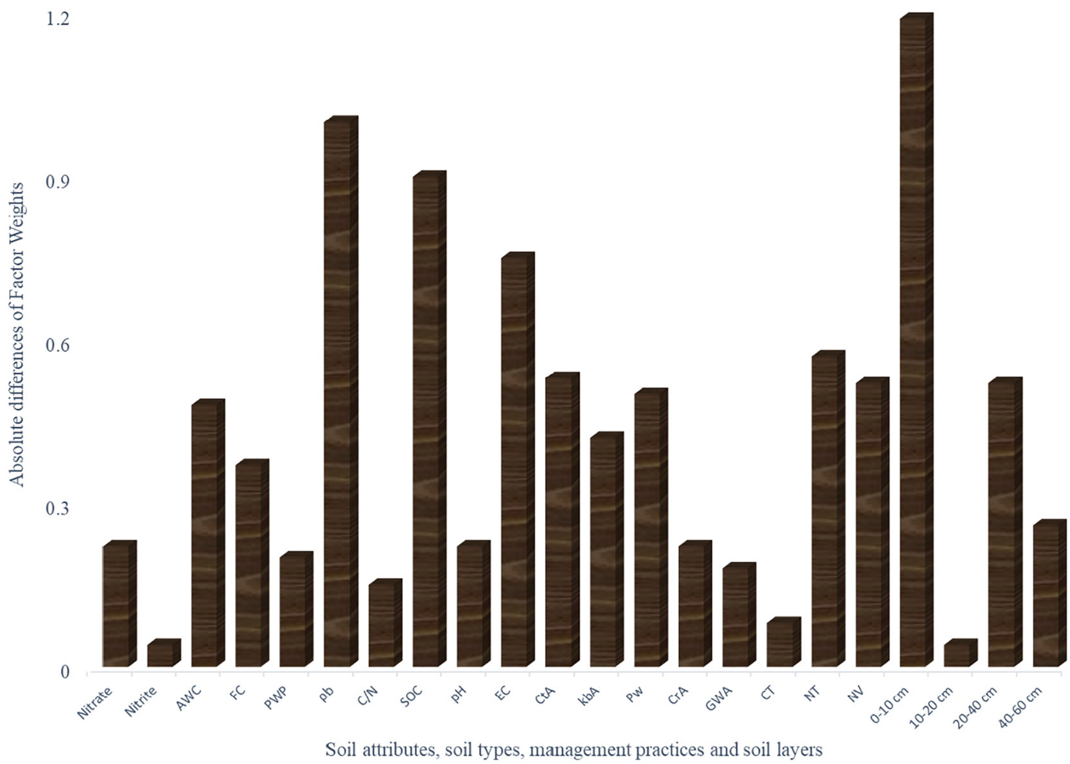

Fig. 2. Absolute differences between year 1 (2012) and year 2 (2013) of factor weights computed by partial least squares regression for soil types, management, soil layers. CrA (Crosby silt loam). kbA (Kibbie fine sandy loam). GWA (Glynwood silt loam). CtA (Crosby Celina silt loams). P_w (Pewamo silty clay loam). AWC: available water capacity (cm^3 of water cm^{-3} of soil). FC: field capacity (cm^3 of water cm^{-3} of soil). PWP: permanent wilting point (cm^3 of water cm^{-3} of soil). NV: natural vegetation. CT: conventional tillage. NT: no till. C/N: carbon/nitrogen ratio. SOC: soil organic carbon (Mg/ ha). Nitrate & nitrite (mg/L). EC: electrical conductivity (μS cm^{-1}). ρ_b: soil bulk density (Mg m^{-3}). Soil layers: 0–10, 10–20, 20–40, 40–60.

because nutrients from the subsoil are possibly recycled to the top soil through plant residue mulch. Hypothetically, low soil ρ_b especially at the surface is indicative of higher biologic activity and SOM, whereas high ρ_b indicates compaction from use of heavy machinery (Lal, 1996). However, a study in the northwest of Ohio investigating axle load effects on soil physical properties, reported that neither tillage nor compaction treatments significantly affected ρ_b (Lal, 1999) In this study, the surface soils especially NT managed had larger factor weight (Fig. 2), a situation attributable to variable soil moisture, microbial activity, bioturbation, erosion, root distribution or biogeochemical cycles (Armenise et al., 2013; de Moraes Sá et al., 2013; Mota et al., 2014). Alternately, relatively higher evapo-transpiration rates on the soil surface and tillage may impact on soil moisture, although this may be lower in NV soils because tree canopy cushions the soil from direct solar insolation. Other studies assert that NT systems not only cause soil compaction and acidification, but also enrich the soil surface with nutrients and organic matter (Lal et al., 1994).

3.2. Soil quality dynamics versus management

Here, two specific questions were addressed: (i) how does management affect soil quality dynamics over a two year time-frame?, (ii) what are the effects of management on crop yields? Tables 2 and 3 inform that soil quality varied with management, with surface soils having a relatively higher soil quality. Both the NT and NV managed soils had CrA soils as the lowest in quality in year one; however for soils under NT management KbA had the highest quality; whereas NV managed soils had both KbA and Pw soils as high quality; similarly CT soil had

Table 2
The Soil Quality Index (SQI) for the 1st year (2012) modeled from soil physical and chemical attributes fitted using partial least squares regression (PLSR).

	CT (0−10)	CT (10−20)	CT (20–40)	CT (40–60)	NV (0–10)	NV (10–20)	NV (20–40)	NV (40–60)	NT (0–10)	NT (10–20)	NT (20–40)	NT (40–60)
Pw	25	10	8	8	15	4	3	5	5	6	5	5
kbA	13	–	–	–	15	5	3	2	26	15	12	9
CtA	10	9	7	7	12	12	10	11	9	5	4	5
GWA	7	7	5	5	13	12	7	3	13	9	10	10
CrA	15	12	9	8	7	2	1	2	11	13	11	10
Total	70	38	29	28	62	35	24	23	64	48	42	39

CrA (Crosby silt loam).
kbA (Kibbie fine sandy loam).
GWA (Glynwood silt loam).
CtA (Crosby Celina silt loams).
P_w (Pewamo silty clay loam).
CT: conventional tillage.
NT: no till.
NV: natural vegetation (Woodland).
Soil depths: 0–10, 10–20, 20–40, 40–60.

Table 3
The Soil Quality Index (SQI) for the 2nd year (2013) modeled from soil physical and chemical attributes fitted using partial least squares regression (PLSR).

	CT (0–10)	CT (10–20)	CT (20–40)	CT (40–60)	NV (0–10)	NV (10–20)	NV (20–40)	NV (40–60)	NT (0–10)	NT (10–20)	NT (20–40)	NT (40–60)
Pw	17	9	8	17	14	7	4	5	4	5	5	4
kbA	11	11	11	11	12	4	3	6	12	7	6	8
CtA	10	8	8	5	7	11	10	11	11	6	5	8
GWA	6	6	7	6	13	11	7	4	12	11	10	7
CrA	14	12	9	8	8	1	1	2	11	12	11	10
Total	58	46	43	49	54	34	25	28	50	41	37	37

CrA (Crosby silt loam).
kbA (Kibbie fine sandy loam).
GWA (Glynwood silt loam).
CtA (Crosby Celina silt loams).
P_w (Pewamo silty clay loam).
CT: conventional tillage.
NT: no till.
NV: natural vegetation (Woodland).
Soil depths: 0–10, 10–20, 20–40, 40–60.

P_w as the highest in quality (Table 2). However, in the 2nd year, Pw surface soil had the highest quality under both CT and NV management; NT managed soils had both kbA ≈ GWA soils equal in quality (Table 3). From a monitoring perspective, although CT managed P_w soils and NT managed kbA soil had the highest quality in both years (Tables 1 and 2), the NT managed kbA surface soil had the largest (14%) soil quality reduction (Table 4). Hypothetically, such occurrence is attributable to fertilizer addition, or higher bioturbation due to the conducive microclimate and aeration for soil biota in CT managed soils. In contrast, the NV managed CtA soil quality reduced by 5%, whereas CrA soil increased by 1%, yet GWA soil did not change. Alternately, CT managed P_w soil quality reduced by 8%.

3.3. Relating soil quality dynamics with crop yields

Within two growing seasons, the correlation between SQI and corn yields was 0.6, whereas soybean was 0.9 confirming the meaningfulness of this metric but also specifically implying that: (i) soybean crops were sensitive to site specific soil characteristics, and (ii) that soybeans were less sensitive to weather variability than corn. Researchers posit that legume-based cropping integrated into conservation tillage systems improve the soil characteristic properties compared with monocultures and plow-based tillage methods (Lal et al., 1994). Legumes and soil microbes play a critical role in the biological nitrogen fixation (Keyser and Li, 1992). However, including soil biota in SQI can be impeded by: (i) inaccuracies in earthworm counts, (ii) difficulty in accounting microbial species diversity, and (iii) inconsistent interpretation of soil respiration tests (Arshad and Martin, 2002; McBratney et al., 2014).

The cropland soil quality for the entire profile (i.e., 0 to 60 cm) based on 1st year data was: (i) NT management was kbA > CrA > GWA > CtA > P_w; and (ii) CT management was P_w > CrA > CtA > GWA (Table 2). However, 1st year corn yield from CrA soil was (9.9 Mg/ha) > GWA soil (8.9 Mg/ha) > CtA soil (6.4 Mg/ha) > P_w soil (2.5 Mg/ha). Alternately, soybean yield from CT managed CtA and kbA soil was higher (2.7 Mg/ha) than from GWA soil (1.40 Mg/ha). In contrast, 2nd year had NT managed CrA soils having a higher soil quality followed by GWA > kbA > CtA > P_w (Table 3), although the CT managed soil quality was P_w > CrA ≈ kbA, CtA > GWA, respectively. Nonetheless, this time had the highest corn yield harvested from kbA soil (11.8 Mg/ha) under NT management, and CT managed P_w soil (10 Mg/ha), whereas highest soybean yield (>3 Mg/ha) were harvested from NT managed CrA and GWA soils.

Despite the minimal soil quality change (Table 4), corn yield from CT managed P_w soil at Auglaize site doubled from 5 Mg/ha in the 1st year to 10 Mg/ha in the 2nd year, and tripled from 2.53 to 8.59 Mg/ha in NT soils. This yield difference may be attributed to meteorological, pedologic (i.e., reduced soil water storage) and agronomic (i.e., low water availability at critical crop growth stage) drought experienced in the 1st year. Besides, soil moisture differences may have contributed to the notably higher soil quality in CT compared with NT managed soils, attributable to higher evapo-transpiration in CT soil that increased nutrient concentration. Yield change was not computed for fields planted with different crops per season.

Besides management, other valuable agronomic information not considered here include: (i) soil organisms, (ii) crop hybrids, (iii) parent material or age of soil, (iv) soil contaminants and erodibility, and (v) climate variability (McBratney et al., 2014; Stockmann et al.,

Table 4
Change in Soil Quality Index (SQI in %) values between year 1 (2012) and 2 (2013).

	CT (0–10)	CT (10–20)	CT (20–40)	CT (40–60)	NV (0–10)	NV (10–20)	NV (20–40)	NV (40–60)	NT (0–10)	NT (10–20)	NT (20–40)	NT (40–60)
Pw	−8	−1	0	9	−1	3	1	0	−1	−1	0	−1
kbA	−2	–	–	–	−3	−1	0	4	−14	−8	−6	−1
CtA	0	−1	1	−2	−5	−1	0	0	2	1	1	3
GWA	−1	−1	2	1	0	−1	0	1	−1	2	0	−3
CrA	−1	0	0	0	1	−1	0	0	0	−1	0	0

CrA (Crosby silt loam).
kbA (Kibbie fine sandy loam).
GWA (Glynwood silt loam).
CtA (Crosby Celina silt loams).
P_w (Pewamo silty clay loam).
CT: conventional tillage.
NT: no till.
NV: natural vegetation (Woodland).
Soil depths: 0–10, 10–20, 20–40, 40–60.

2013). Jobbágy and Jackson (2001) argue that models depicting crop yields should incorporate: (i) biogeochemical cycling, (ii) plant tissue stoichiometry, (iii) biomass cycling rates, and (iv) plant root distributions. This study exemplifies a new quantitative technique that synthesizes soil information for systematic monitoring of soil quality in both the vertical and horizontal dimension, information pertinent for developing site specific best management practices (BMPs) strategies to promote sustainable agronomic intensification. The goal of sustainable agronomic intensification is to produce more per unit area, with improved crop varieties, less wastes, and eco-efficient inputs of fertilizer, water, energy, time and soil (Lal, 2013, 2016). Indeed, information on soil quality variability with depth is critical for precision agriculture and developing new site specific BMPs for increasing agronomic yield in the vertical (i.e., farming) dimension, because dwindling agricultural lands limit horizontal expansion.

4. Conclusions

This paper presents a new PLSR based SQI for monitoring soil quality. The salient findings are (i) the SQI correlated highly with corn and soybean yields, (ii) CT managed soils had the highest quality in both years; followed by NT soils in the 1st year and NV in the second, (iii) P_w soil under CT management was consistently of a higher quality than CrA, kbA, CtA, and GWA soil, respectively, and (iv) ρ_b, SOC, AWC, and EC were the significant soil parameters influencing soil quality. Because changes in magnitude and direction of soil processes and functions are important facets of ecosystem response to transitions in land management, models depicting these dynamics may provide critical information for guiding policy. Future research should investigate techniques for interpolating this SQI, because soil quality varies with scale and a field can have several soil types. The temporal scale at which soil quality significantly changes will be a subject of another study.

Acknowledgements

This research is part of a regional collaborative project supported by the USDA-NIFA, Award No. 2011-68002-30190, "Cropping Systems Coordinated Agricultural Project (CAP): Climate Change, Mitigation, and Adaptation in Corn-based Cropping Systems". Project Web site: sustainablecorn.org. The author acknowledges the invaluable feedback from the reviewers.

References

Andrews, S.S., Carroll, C.R., 2001. Designing a soil quality assessment tool for sustainable agroecosystem management. Ecol. Appl. 11, 1573–1585.
Andrews, S.S., Karlen, D.L., Mitchell, J.P., 2002a. A comparison of soil quality indexing methods for vegetable production systems in Northern California. Agric. Ecosyst. Environ. 90, 25–45.
Andrews, S.S., Mitchell, J.P., Mancinelli, R., Karlen, D.L., Hartz, T.K., Horwath, W.R., Pettygrove, G.S., Scow, K.M., Munk, D.S., 2002b. On-farm assessment of soil quality in California's central valley. Agron. J. 94, 12–23.
Armenise, E., Redmile-Gordon, M.A., Stellacci, A.M., Ciccarese, A., Rubino, P., 2013. Developing a soil quality index to compare soil fitness for agricultural use under different managements in the Mediterranean environment. Soil Tillage Res. 130, 91–98.
Arshad, M.A., Martin, S., 2002. Identifying critical limits for soil quality indicators in agroecosystems. Agric. Ecosyst. Environ. 88, 153–160.
Blanco-Canqui, H., Lal, R., 2007. Impacts of long-term wheat straw management on soil hydraulic properties under no-tillage. Soil Sci. Soc. Am. J. 71, 1166–1173.
Blecker, S.W., Stillings, L.L., Amacher, M.C., Ippolito, J.A., Decrappeo, N.M., 2012. Development of vegetation based soil quality indices for mineralized terrane in arid and semi-arid regions. Ecol. Indic. 20, 65–74.
Bouma, J., 2015. Reaching out from the soil-box in pursuit of soil security. Soil Sci. Plant Nutr. 1–10.
Bouma, J., McBratney, A., 2013. Framing soils as an actor when dealing with wicked environmental problems. Geoderma 200–201, 130–139.
Brown, D.J., Shepherd, K.D., Walsh, M.G., Mays, M.D., Reinsch, T.G., 2006. Global soil characterization with VNIR diffuse reflectance spectroscopy. Geoderma 132, 273–290.
Bünemann, E.K., Bongiorno, G., Bai, Z., Creamer, R.E., De Deyn, G., de Goede, R., Fleskens, L., Geissen, V., Kuyper, T.W., Mäder, P., Pulleman, M., Sukkel, W., van Groenigen, J.W., Brussaard, L., 2018. Soil quality – a critical review. Soil Biol. Biochem. 120, 105–125.
Clement, C.R., 1996. A simple and reliable tension table. J. Soil Sci. 17.
Dane, J.H., Hopmans, J.W., 2002. Water retention and storage. In: Dane, J.H., Topp, G.C. (Eds.), Methods of Soil Analysis: Part 4 Physical Methods. Agronomy Monograph, pp. 675–719 Madison, WI.
de Moraes Sá, J.C., Bürkner dos Santos, J., Lal, R., de Moraes, A., Tivet, F., Machado Sá, M.F., Briedis, C., de Oliveira Ferreira, A., Eurich, G., Farias, A., Friedrich, T., 2013. Soil-specific inventories of landscape carbon and nitrogen stocks under no-till and Native vegetation to estimate carbon offset in a subtropical ecosystem. Soil Sci. Soc. Am. J. 77, 2094–2110.
de Paul Obade, V., Lal, R., 2013. Assessing land cover and soil quality by remote sensing and geographical information systems (GIS). Catena 104, 77–92.
de Paul Obade, V., Lal, R., 2014a. Soil quality evaluation under different land management practices. Environ. Earth Sci. 72, 4531–4549.
de Paul Obade, V., Lal, R., 2014b. Using meta-analyses to assess pedo-variability under different land uses and soil management in central Ohio, USA. Geoderma 232–234, 56–68.
de Paul Obade, V., Lal, R., 2016a. A standardized soil quality index for diverse field conditions. Sci. Total Environ. 541, 424–434.
de Paul Obade, V., Lal, R., 2016b. Towards a standard technique for soil quality assessment. Geoderma 265, 96–102.
de Paul Obade, Vincent, Moore, Richard, 2018. Synthesizing water quality indicators from standardized geospatial information to remedy water security challenges: a review. Environ. Int. 119, 220–231.
de Paul Obade, V., Lal, R., Chen, J., 2013. Remote sensing of soil and water quality in agroecosystems. Water Air Soil Pollut. 224, 1–27.
De Vos, B., Van Meirvenne, M., Quataert, P., Deckers, J., Muys, B., 2005. Predictive quality of pedotransfer functions for estimating bulk density of forest soils. Soil Sci. Soc. Am. J. 69, 500–510.
DeForest, J.L., Smemo, K.A., Burke, D.J., Elliott, H.L., Becker, J.C., 2012. Soil microbial responses to elevated phosphorus and pH in acidic temperate deciduous forests. Biogeochemistry 109, 189–202.
Dick, W., 1983. Organic carbon, nitrogen, and phosphorus concentrations and pH in soil profiles as affected by tillage intensity. Soil Sci. Soc. Am. J. 47, 102–107.
Doran, J.W., Parkin, T.B., 1994. Defining and assessing soil quality. In: Doran, J.W., Coleman, D.C., Bezdicek, D.F., Stewart, B.A. (Eds.), Defining Soil Quality for a Sustainable Environment. SSSA, Inc., Madison, Wisconsin, USA.
FAO, 2013. The State of Food Insecurity in the World. The Multiple Dimensions of Food Security. Food and Agricultural Organization of the United Nations, Rome.
Fierer, N., Bradford, M.A., Jackson, R.B., 2007. Toward an ecological classification of soil bacteria. Ecology 88, 1354–1364.
Finzi, A.C., Cole, J.J., Doney, S.C., Holland, E.A., Jackson, R.B., 2011. Research frontiers in the analysis of coupled biogeochemical cycles. Front. Ecol. Environ. 9, 74–80.
Jemai, I., Ben Aissa, N., Ben Guirat, S., Ben-Hammouda, M., Gallali, T., 2013. Impact of three and seven years of no-tillage on the soil water storage, in the plant root zone, under a dry subhumid Tunisian climate. Soil Tillage Res. 126, 26–33.
Jobbágy, E., Jackson, R., 2001. The distribution of soil nutrients with depth: global patterns and the imprint of plants. Biogeochemistry 53, 51–77.
Jobbágy, E.G., Jackson, R.B., 2004. The uplift of soil nutrients by plants: biogeochemical consequences across scales. Ecology 85, 2380–2389.
Karlen, D.L., Mausbach, M.J., Doran, J.W., Cline, R.G., Harris, R.F., Schuman, G.E., 1997. Soil quality: a concept, definition, and framework for evaluation. Soil Sci. Soc. Am. J. 61, 4–10.
Karlen, D.L.K., Gardner, J.C., Rosek, M.J., 1998. A soil quality framework for evaluating the impact of CRP. JPA 11, 56–60.
Karlen, D.L., Tomer, M.D., Neppel, J., Cambardella, C.A., 2008. A preliminary watershed scale soil quality assessment in north central Iowa, USA. Soil Tillage Res. 99, 291–299.
Keyser, H., Li, F., 1992. Potential for increasing biological nitrogen fixation in soybean. Plant Soil 141, 119–135.
Kladivko, E.J., Helmers, M.J., Abendroth, L.J., Herzmann, D., Lal, R., Castellano, M.J., Mueller, D.S., Sawyer, J.E., Anex, R.P., Arritt, R.W., Basso, B., Bonta, J.V., Bowling, L.C., Cruse, R.M., Fausey, N.R., Frankenberger, J.R., Gassman, P.W., Gassmann, A.J., Kling, C.L., Kravchenko, A., Lauer, J.G., Miguez, F.E., Nafziger, E.D., Nkongolo, N., O'Neal, M., Owens, L.B., Owens, P.R., Scharf, P., Shipitalo, M.J., Strock, J.S., Villamil, M.B., 2014. Standardized research protocols enable transdisciplinary research of climate variation impacts in corn production systems. J. Soil Water Conserv. 69, 532–542.
Klute, A., 1986. Water retention: laboratory methods. Methods of Soil Analysis: Part 1—Physical and Mineralogical Methods SSSA Book Series, pp. 635–662.
Klute, A., Dirksen, C., 1986. Hydraulic conductivity and diffusivity: laboratory methods. Methods of Soil Analysis: Part 1—Physical and Mineralogical Methods SSSA Book Series, pp. 687–734.
Lal, R., 1996. Deforestation and land-use effects on soil degradation and rehabilitation in western Nigeria. Soil chemical properties. Land Degrad. Dev. 7, 87–98.
Lal, R., 1999. Soil compaction and tillage effects on soil physical properties of a mollic ochraqualf in northwest Ohio. J. Sustain. Agric. 14, 53–65.
Lal, R., 2002. Soil carbon dynamics in cropland and rangeland. Environ. Pollut. 116, 353–362.
Lal, R., 2004. Soil Quality in Industrialized and Developing Countries - Similarities and Differences.
Lal, R., 2009. Tragedy of the Global Commons: Soil, Water and Air.
Lal, R., 2013. Climate-strategic agriculture and the water-soil-waste nexus. J. Plant Nutr. Soil Sci. 176, 479–493.
Lal, R., 2014. Soil Carbon Management and Climate Change. Springer International Publishing Switzerland.
Lal, R., 2016. Soil health and carbon management. Food Energy Secur. 5, 212–222.
Lal, R., Mahboubi, A.A., Fausey, N.R., 1994. Long-term tillage and rotation effects on properties of a Central Ohio soil. Soil Sci. Soc. Am. J. 58, 517–522.

Lal, R., Delgado, J.A., Gulliford, J., Nielsen, D., Rice, C.W., Van Pelt, R.S., 2012. Adapting agriculture to drought and extreme events. J. Soil Water Conserv. 67, 162A–166A.
Larson, W.E., Pierce, F.J., 1994. The Dynamics of soil quality as a measure of sustainable management. In: Doran, J.W., Coleman, D.C., Bezdicek, D.F., Stewart, B.A. (Eds.), Defining Soil Quality for a Sustainable Environment, pp. 37–51.
McBratney, A., Field, D.J., Koch, A., 2014. The dimensions of soil security. Geoderma 213, 203–213.
Mehmood, T., Martens, H., Saebo, S., Warringer, J., Snipen, L., 2011. A partial least squares based algorithm for parsimonious variable selection. Algorithm Mol. Biol. 6.
Mehmood, T., Liland, K.H., Snipen, L., Saebo, S., 2012. A review of variable selection methods in partial least squares regression. Chemom. Intell. Lab. Syst. 118, 62–69.
Mota, J.C.A., Alves, C.V.O., Freire, A.G., de Assis Júnior, R.N., 2014. Uni and multivariate analyses of soil physical quality indicators of a Cambisol from Apodi Plateau – CE, Brazil. Soil Tillage Res. 140, 66–73.
Nelson, D.W., Sommers, L.E., 1996. Total carbon, organic carbon, and organic matter. In: Sparks, D.L., et al. (Eds.), Am. Soc. of Agron, 2nd ed. SSA, Madison, WI, pp. 961–1010.
Nguyen, T.T., Verdoodt, A., Van, Y.T., Delbecque, N., Tran, T.C., Van Ranst, E., 2015. Design of a GIS and multi-criteria based land evaluation procedure for sustainable land-use planning at the regional level. Agric. Ecosyst. Environ. 200, 1–11.
Nortcliff, S., 2002. Standardisation of soil quality attributes. Agric. Ecosyst. Environ. 88, 161–168.
Obade, V.d.P., 2012. Review article: remote sensing, surface residue cover and tillage practice. J. Environ. Prot. 3, 211–217.
Ohlson, K., 2014. The Soil Will Save Us: How Scientists, Farmers, and Foodies Are Healing the Soil to Save the Planet. Rodale.
Paz-Ferreiro, J., Fu, S., 2016. Biological indices for soil quality evaluation: perspectives and limitations. Land Degrad. Dev. 27, 14–25.
Peech, M., 1965. Hydrogen ion activity. ASA Monograph, Part 2 ed. ASA, Madison, WI, pp. 914–925.
Rosa, D.d.l., 2005. Soil quality evaluation and monitoring based on land evaluation. Land Degrad. Dev. 16, 551–559.
Stockmann, U., Adams, M.A., Crawford, J.W., Field, D.J., Henakaarchchi, N., Jenkins, M., Minasny, B., McBratney, A.B., de Courcelles, V.D., Singh, K., Wheeler, I., Abbott, L., Angers, D.A., Baldock, J., Bird, M., Brookes, P.C., Chenu, C., Jastrowh, J.D., Lal, R., Lehmann, J., O'Donnell, A.G., Parton, W.J., Whitehead, D., Zimmermann, M., 2013. The knowns, known unknowns and unknowns of sequestration of soil organic carbon. Agric. Ecosyst. Environ. 164, 80–99.
Stockmann, U., Minasny, B., McBratney, A.B., 2014. How fast does soil grow? Geoderma 216, 48–61.
Topp, G.C., Ferre, P.A., 2002. Water content. In: Dane, J.H., Topp, G.C. (Eds.), Methods of Soil Analysis: Part 4 Physical Methods. Agronomy Monograph. SSSA, Madison, WI, pp. 417–422.
Vollmer, D., Regan, H.M., Andelman, S.J., 2016. Assessing the sustainability of freshwater systems: a critical review of composite indicators. Ambio 45, 765–780.
Vollmer, D., Shaad, K., Souter, N.J., Farrell, T., Dudgeon, D., Sullivan, C.A., Fauconnier, I., MacDonald, G.M., McCartney, M.P., Power, A.G., McNally, A., Andelman, S.J., Capon, T., Devineni, N., Apirumanekul, C., Ng, C.N., Rebecca Shaw, M., Wang, R.Y., Lai, C., Wang, Z., Regan, H.M., 2018. Integrating the social, hydrological and ecological dimensions of freshwater health: the freshwater health index. Sci. Total Environ. 627, 304–313.
Wienhold, B.J., Andrews, S.S., Karlen, D.L., 2004. Soil quality: a review of the science and experiences in the USA. Environ. Geochem. Health 26, 89–95.
Zhang, S., Zhao, T.B., Wang, J., Qu, X.L., Chen, W., Han, Y., 2013. Determination of fluorine, chlorine and bromine in household products by means of oxygen bomb combustion and ion chromatography. J. Chromatogr. Sci. 51, 65–69.